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# SOC estimation for LiFePO4 battery in EVs using recursive least-squares with multiple adaptive forgetting factors

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### Abstract
This work presents a novel technique which is simple yet effective in estimating electric model parameters and state-of-charge (SOC) of the LiFePO4 battery. Unlike the well-known recursive least-squares-based algorithms with single constant forgetting factor, this technique employs multiple adaptive forgetting factors to provide the capability to capture the different dynamics of model parameters. The validity of the proposed method is verified through experiments using actual driving cycles.

### Keywords
estimation, lifepo4, battery, evs, recursive, least, soc, squares, factors, multiple, adaptive, forgetting

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# SOC Estimation for $LiFePO_4$ Battery in EVs Using Recursive Least-Squares with Multiple Adaptive Forgetting Factors

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***Abstract*- This work presents a novel technique which is simple yet effective in estimating electric model parameters and state-of-charge (SOC) of the $LiFePO_4$ battery. Unlike the well-known recursive least-squares-based algorithms with single constant forgetting factor, this technique employs multiple adaptive forgetting factors to provide the capability to capture the different dynamics of model parameters. The validity of the proposed method is verified through experiments using actual driving cycles.**

***Keywords*- *State-of-Charge, $LiFePO_4$ Battery, Recursive Least Square, Multiple Adaptive Forgetting Factors***

## I. INTRODUCTION

Electric vehicles have been well recognized because of their contribution in the promising future of emission-free transportation means. The core of the electric vehicles is the battery storage system which plays an important role in the safety and price of the vehicles. Therefore, there is a necessity to develop an effective battery management system in the field of electrification. Various advanced methods have been proposed and applied to cope with difficulties in estimating the states of battery in the storage system [1].

Among these effective methods, recursive least-squares (RLS) algorithm applied on electrical-equivalent battery model has been well proposed and implemented in the battery management system in order to estimate the states of the $LiFePO_4$ battery online [1, 2]. In order to adapt with dynamic changes of the battery under driving cycles, RLS with a constant forgetting factor has been used. However, the parameters to be estimated for the battery model have different dynamic characteristics. Hence, assigning a single constant forgetting factor may not provide accurate estimations of all battery model parameters and will likely cause divergence in the estimation. To further improve the performance of RLS algorithm, a novel technique employing multiple adaptive forgetting factors is proposed for the first time in this paper.

## II. BATTERY MODEL AND ESTIMATION ALGORITHM

### A. Battery Model

In order to accurately model the $LiFePO_4$ battery, an equivalent circuit consisting of an open-circuit voltage (OCV) source, an internal resistance, and two networks of resistance and capacitance (R-RC-RC) connected in series is required [3]. However, this model requires heavy computations due to the presence of two capacitors. To simplify the model for the sake of fast and feasible implementation, it can be transformed into the one which is depicted in Fig. 1. A detailed explanation of the validity and effectiveness of this transformation can be found elsewhere [4].

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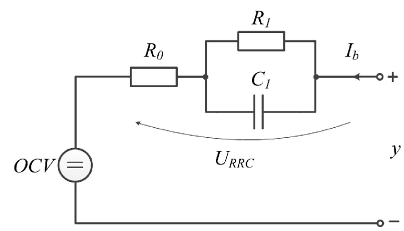


Fig. 1 Electrical model for $LiFePO_4$ battery

### B. Estimation Algorithm

In order to apply the proposed RLS technique, an auto regressive exogenous (ARX) model is required. To do so, firstly the transfer function of the battery impedance is expressed in s-domain as follows:

$$G(s) = \frac{U_{RRC}(s)}{I(s)} = R_0 + \frac{R_1}{1 + sR_1C_1} \tag{1}$$

where $U_{RRC}$ represents the dynamic voltage drop of the battery across the series resistance and the RC section. Then, the system is discretised with a sampling time $T_s$ through the simple forward-difference transformation to avoid complexity. Finally, the ARX model is formulated as below:

$$y_k = \theta_k^T \cdot \phi_k \tag{2}$$

where $$\theta_k = \left[b_{0,k};\quad b_{1,k};\quad a_{1,k};\quad OCV_k\right] \tag{3}$$

$$\phi_k = \left[I_k;\quad I_{k-1};\quad \left(OCV_{k-1} - y_{k-1}\right);\quad 1\right] \tag{4}$$

$$b_0 = R_0 \tag{5}$$

$$b_1 = -R_0 + \frac{T_s}{C_1} + \frac{T_s \cdot R_0}{R_1 \cdot C_1} \tag{6}$$

$$a_1 = \frac{T_s}{R_1 \cdot C_1} - 1 \tag{7}$$

For the conventional RLS, usually a single forgetting factor $\lambda$ is assigned for all the parameters although the dynamic behaviour of each parameter is different from the others under the same conditions of current, voltage, and temperature of the battery. This might result in an inaccurate parameters identification which consequently causes a poor SOC estimation. To avoid this issue, we propose to employ

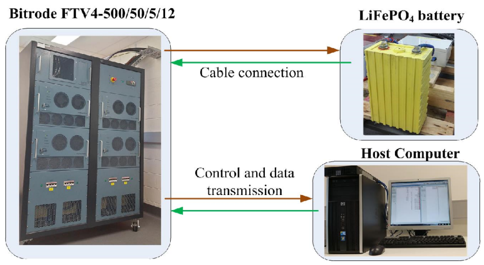


Fig. 2 Test bench configuration

multiple adaptive forgetting factors $\lambda_{i,k}$ in the computation procedure of the RLS estimation as follows [5, 6]:

$$\lambda_{i,k} = 1 - \frac{1}{1 + \zeta_i \big/ \phi_{i,k}^T \cdot P_{i,k-1} \cdot \phi_{i,k}} \tag{8}$$

$$L_{i,k} = \frac{P_{i,k-1} \cdot \phi_{i,k}}{\lambda_{i,k} + \phi_{i,k}^T \cdot P_{i,k-1} \cdot \phi_{i,k}} \tag{9}$$

$$P_{i,k} = 1 \big/ \lambda_{i,k} \left(1 - L_{i,k} \cdot \phi_{i,k}^T\right) P_{i,k-1} \tag{10}$$

$$\boldsymbol{\theta}_k = \boldsymbol{\theta}_{k-1} + \boldsymbol{L}_{mul,k}\left(y_k - \boldsymbol{\phi}_k^T \cdot \boldsymbol{\theta}_{k-1}\right) \tag{11}$$

where $$\boldsymbol{L}_{mul,k} = \frac{1}{1 + \sum_{i=1}^{4} \frac{P_{i,k-1} \cdot \phi_{i,k}^2}{\lambda_{i,k}}} \begin{bmatrix} P_{1,k-1} \cdot \phi_{1,k} / \lambda_{1,k} \\ P_{2,k-1} \cdot \phi_{2,k} / \lambda_{2,k} \\ P_{3,k-1} \cdot \phi_{3,k} / \lambda_{3,k} \\ P_{4,k-1} \cdot \phi_{4,k} / \lambda_{4,k} \end{bmatrix} \tag{12}$$

$\boldsymbol{L}_{mul,k}$ and $L_{i,k}$ are the updated gain of estimated parameters vector $\boldsymbol{\theta}_k$ and its component, respectively. Similarly, $\lambda_i$ and $P_{i,k}$ are the forgetting factor and the covariance error of each component of vector $\boldsymbol{\theta}_k$ while $\zeta_i$ is the tunning parameter for each forgetting factor.

## III. Experimental Results

A 40Ah $LiFePO_4$ battery is used for the experiments which are carried out at 20°C. The test bench configuration is illustrated in Fig. 2. A programmable Bitrode machine with very high accuracy is used to charge/discharge the battery with maximum current of 500A and maximum voltage of 12V. Current pulses are applied to construct the battery's characteristic curve of OCV versus SOC. Then, experiments using current patterns and battery terminal voltage of actual driving cycle are conducted to verify the validity of the proposed technique as shown in Fig. 3. The battery parameters are directly identified based on the estimation of the parameters vector $\boldsymbol{\theta}_k$. The SOC is obtained from the estimated OCV via a look-up table built from the experimental OCV-SOC curve. It can be seen in Fig. 4 (a) that estimation of the resistance $R_0$ is constant after convergence which perfectly describes the limited conductance of the contact, the inter-cell connections, and the electrolyte. In Fig. 4 (b), the estimation of the charge-transfer resistance $R_1$ is dynamic corresponding

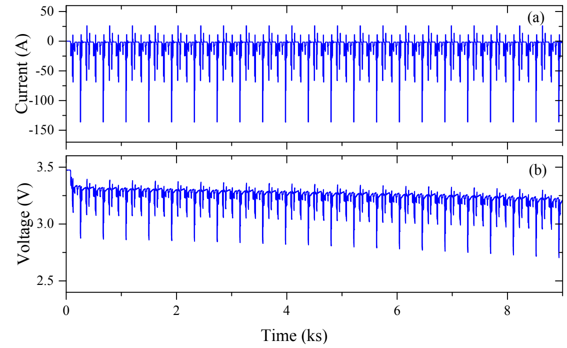


Fig. 3 Actual driving cycle load profile: (a) Current, (b) Voltage

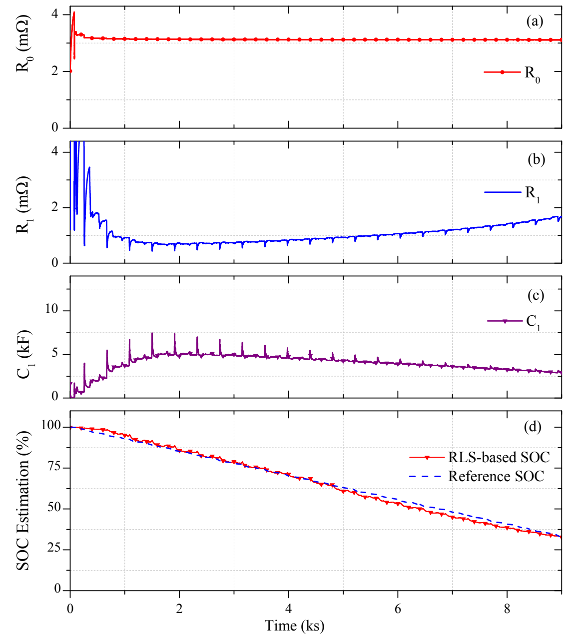


Fig. 4 Experimental results: (a-c) parameters estimation; (d) SOC estimation

to the change of the current amplitude and SOC as expected. Fig. 4 (d) shows the result of SOC estimation obtained by the proposed method compared to the reference SOC obtained from Coulomb counting with an accurate initial value. As can be seen, the estimated SOC tracks the reference value well with root-mean-square error (RMSE) of 0.019.

## IV. Conclusion

In this work, the RLS technique with multiple adaptive forgetting factors has been proposed for the estimation of the dynamic parameters and SOC of $LiFePO_4$ battery. The validity of the method has been confirmed by accurate SOC estimation results with RMSE of 0.019. In addition, the feasibility of this method has been proven by the simplicity of the model and the light scalar computations in algorithm.

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